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R&D and Productivity Growth

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CBO

R&D and Productivity Growth: A Background Paper

June 2005

The Congress of the United States ■ Congressional Budget Office

Note

Numbers in the text and tables may not add up to totals because of rounding.

Preface

The Congressional Budget Office (CBO) regularly reviews its estimating methods to consider issues that could affect its economic forecast and projections. This background paper examines how spending for research and development influences economic growth and evaluates whether those effects should be incorporated in the model that CBO uses for its 10-year economic outlook. In keeping with CBO's mandate to provide objective, impartial analysis, this paper makes no recommendations.

Robert Arnold of CBO's Macroeconomic Analysis Division prepared the paper under the supervision of John Peterson and Robert Dennis. Brian Mathis provided research assistance. Within CBO, Ufuk Demiroglu, Douglas Hamilton, Arlene Holen, Kim Kowalewski, and Benjamin Page provided useful comments. Jacques Mairesse of CREST-INSEE (Centre de Recherches en Economie et Statistique-Institut Nationale de la Statistique et des Etudes Economiques) and Leo Sveikauskas of the Bureau of Labor Statistics read the paper and made valuable suggestions. (The assistance of external reviewers implies no responsibility for the final product, which rests solely with CBO.)

Leah Mazade edited the paper, and Maureen Costantino prepared it for publication and designed the cover. Lenny Skutnik printed copies for distribution, and Annette Kalicki and Simone Thomas prepared the electronic version for CBO's Web site (www.cbo.gov).

Douglas Holtz-Eakin
Director

June 2005

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Summary and Introduction

Technological change is an important determinant of long-run productivity growth and therefore of increases in living standards over time. Advances in technology arise from innovation, which is the process of inventing new products, improving existing products, and reducing the cost of producing existing goods and services. Research and development (R&D) is the term applied to the efforts of scientists, engineers, entrepreneurs, inventors, and even crackpots who develop new knowledge or devise better ways of doing things and then reap the rewards when they are successful.

Innovation is a highly uncertain undertaking. New knowledge accumulates in a way that is neither predictable, steady, nor continuous. Entrepreneurs may commit substantial amounts of time and money to the search for a groundbreaking invention and at the end of the day have nothing to show for it. Other innovators may discover a new product by a stroke of luck and amass a fortune as a result. Although innovation is a poorly understood process characterized by a large element of chance, it is still influenced by economic forces and incentives. In particular, inventors (including firms) are motivated by the profits that are expected to flow from a successful innovation, and those profits in turn spur further innovation.

Many analysts, aware of the importance of research and development for new discoveries, have studied the connection between spending for R&D and productivity growth. As a result, a large number of empirical studies estimate the effect of R&D investment on such growth. The estimates from that research span a wide range: some studies have found that R&D's effect on productivity is essentially zero, whereas others have found that its effect is substantial and that it exceeds that of other types of investment by a large margin. Most of the estimates, however, lie somewhere between the two extremes, and as a result, a consensus has formed around the view that R&D spending has a significantly positive effect on productivity growth, with a rate of return that is about the same size as (or perhaps slightly larger than) the rate of return on conventional investments. That consensus is not surprising: most analysts would expect privately funded R&D to be about as profitable as other uses of corporate funds because otherwise firms would not continually undertake R&D projects.

This Congressional Budget Office (CBO) paper is not meant to be a survey of the empirical literature relating to R&D and productivity—many such studies already exist. Instead, the paper draws on previous studies, including past surveys, to offer information bearing on three questions related to R&D and productivity growth. First, is R&D an important factor in explaining the growth of total factor productivity (TFP) at the economywide level? Second, if R&D *is* an important factor, how great is its impact? In practice, the main evidence related to those questions consists of econometric estimates of the elasticity of output with respect to R&D, which is defined as the percentage change in output that would be expected from a 1 percent increase in R&D investment. The majority of this paper examines previous studies and surveys to determine a reasonable estimate of the R&D elasticity for the U.S. economy.

The third question that the paper examines is, given the shortcomings of the available data, is it worthwhile to add R&D spending to existing models of the economy? CBO uses several such long-run models to forecast growth of gross domestic product (GDP) and to analyze policy options, and TFP growth is an important variable in each one. Although economics has yet to fully explain the determinants of TFP growth, even a cursory glance at the empirical literature suggests that R&D plays an important role. If so, models of long-run economic

growth will benefit from an explicit treatment of R&D, especially if the addition of that factor allows those models to better explain economic history.

Following are the major findings reported in this paper.

- The consensus view of the link between R&D and productivity is probably the correct one: it is quite likely that R&D has a positive impact on productivity, with a rate of return that is at least equal to the return on other types of investment. However, shortcomings of the available data and the difficulties associated with current estimating methods make it difficult to identify with any precision the size of the contribution that R&D makes. Thus, estimates of the R&D elasticity span a wide range; they depend on the sample, the estimating method, and the period being considered.

- One aspect of the results of this analysis that is of interest to modelers is the divergence between cross-sectional and time-series estimates. The strongest results in the literature come from studies that use cross-sectional data—that is, studies that relate differences in levels of productivity among firms to differences in their spending for R&D. Results from studies that examine the link between R&D spending and TFP growth through the use of time-series data and results from research that employs more aggregated data are considerably weaker, with estimated coefficients that are much smaller and often statistically insignificant. In principle, cross-sectional and time-series methods should yield the same answer.

- Some evidence suggests that R&D is subject to "spillovers," which are benefits that accrue to firms, industries, and possibly nations other than the one performing (and paying for) the research. Because of difficulties in measuring and estimating the extent of spillovers, that evidence is more speculative than the evidence relating to estimates of the return to the firm or industry that performs the R&D.

- Studies that use growth accounting methods—meaning those that estimate the contribution made to economic growth by factors of production such as labor and capital—have found that R&D spending has made a small, steady contribution to economic growth in the United States during the post-World War II period. Those studies have also found that R&D does not help to explain major shifts in the data on productivity growth, such as the post-1973 slowdown or the post-1995 acceleration.

Two caveats about the scope of this paper are in order. First, by necessity, virtually all of the empirical studies in the R&D literature use a limited definition of research and development. Analysts who study technological change prefer a broad measure of R&D that includes any effort that increases the state of knowledge and might therefore aid innovation. Since it is impossible to measure every activity that boosts a country's stock of knowledge, the available data include only formal R&D spending by businesses—which reflects only a small fraction of true R&D. Hence, this paper examines the question that most studies in the empirical literature address: What is the impact of formal R&D on productivity?

A second caveat is that this paper focuses almost exclusively on R&D spending that is funded by private entities. Publicly funded R&D is not addressed here largely because CBO has already examined the link between public R&D and productivity in two earlier reports (CBO 1991, 1998). In those papers, which surveyed the empirical literature, CBO concluded that there was little evidence that federal R&D spending had a significant and direct impact on

private productivity growth. That conclusion, however, does not mean that federal expenditures are a waste of funds. Much federal R&D spending serves the mission of a particular agency—space exploration or national defense, for example—supporting activities that would not be performed by private companies. Furthermore, there is evidence that privately funded R&D benefits from basic science research that is carried out by government employees (or academic scientists who have government support) and that is available in the public domain.

Trends in R&D Investment

In 2003, R&D expenditures in the United States totaled $284 billion, of which 30 percent ($85 billion) was funded by the federal government and 70 percent ($199 billion) was funded by private industry, universities, and nonprofit institutions. In real (inflation-adjusted) terms, R&D spending has steadily increased in the United States, growing since the early 1950s at an average annual rate of 4.6 percent (see Figure 1). Since the late 1980s, however, as federal spending reached a plateau, all of that growth has come from the private sector.[1]

Spending for R&D is small relative to the size of the overall economy, varying between 2 percent and 3 percent of GDP since the 1960s (see Figure 2). Although that share has been roughly constant during the past three decades, a profound shift has occurred in the pattern of R&D investment during that time, a move away from federal spending and toward private spending. Changes in R&D investment in space- and defense-related research explain most of the fluctuation in total federal R&D spending. The surge in such spending for the space program (and defense) can be seen clearly during the 1960s, as can the decline in federal R&D spending during the 1980s, interrupted only slightly by increases in defense-related R&D. (For more details, see CBO's 1991 report.)

Traditionally, R&D has been divided into three categories: basic research, applied research, and development.

- **Pure basic research** is experimental and theoretical work that is undertaken not to reap long-term benefits but to advance the state of knowledge.[2]

- **Applied research** is original work to acquire new knowledge that is undertaken with a specific application in view. It aims to determine possible uses for the findings of basic research or to determine new ways of achieving specific, predetermined objectives.

- **Experimental development** is systematic work using existing knowledge gained from research or practical experience that is directed toward producing new materials, products, or devices; installing new processes, systems, or services; or substantially improving what has been produced or installed in the past.

Development makes up the largest share of private R&D spending: between 1953 and 2001, development averaged about 71 percent, followed by applied research (23 percent) and basic

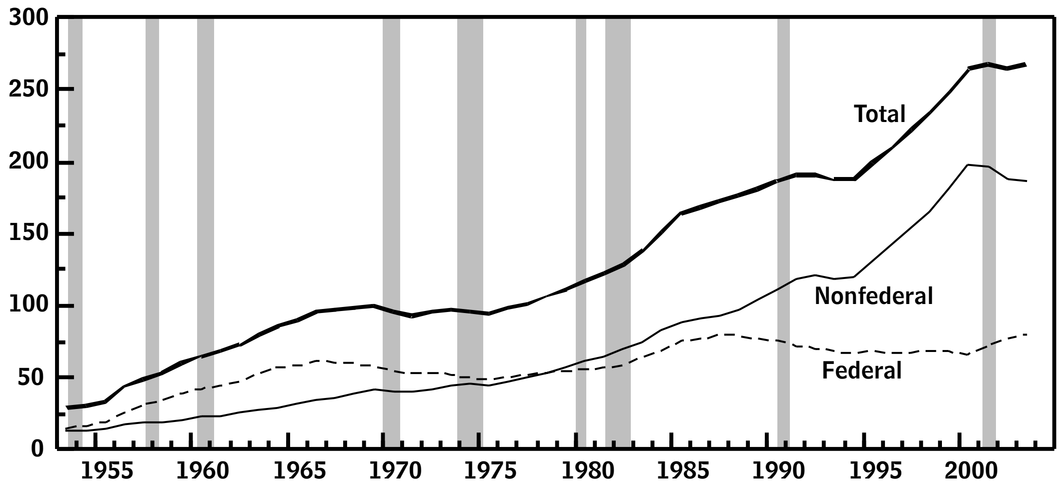
1. Data on R&D are collected by the National Science Foundation and, as noted earlier, capture only a small portion of actual innovation in the economy. However, those data are presented here because they are used by most of the empirical studies reviewed in this paper.

2. Definitions come from the Australian Industry Commission (1995). CBO (1991, p. 78) uses definitions from the National Science Board.

Figure 1.

Federal and Nonfederal Spending for R&D, 1953 to 2002

(Billions of chained 2000 dollars)



Source: Congressional Budget Office based on data from the National Science Foundation.

Note: R&D = research and development.

research (5 percent). Those shares have been relatively stable since 1953, with no steady upward or downward movement over time.

Of the $182 billion of private spending for R&D in 2001 (the last year for which a breakdown is available), 60 percent ($109 billion) funded R&D that was performed in the manufacturing sector (see Figure 3). Among manufacturers, companies in the computer and electronics industries, including semiconductor manufacturers, accounted for the largest share (38 percent), followed by companies in the transportation equipment (19 percent) and chemical (16 percent) industries. None of the "other manufacturing" industries (for example, machinery, paper products, and medical equipment) made up more than 6 percent of the manufacturing total in 2001.

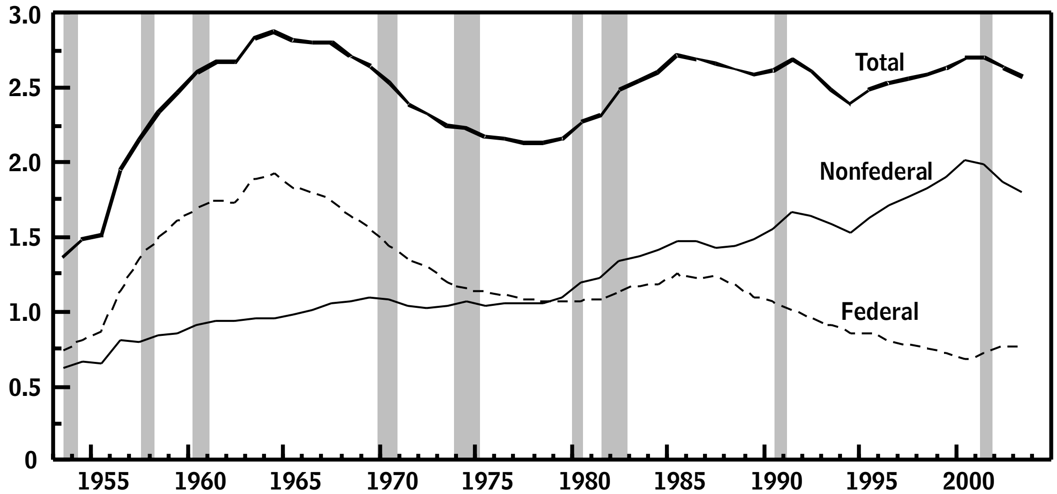
Among nonmanufacturing industries, which spent $72 billion on R&D activities in 2001, the trade sector accounted for the largest share (34 percent of the total).[3] Following trade were professional, scientific, and technical services, which spent $23 billion (31 percent), and software, at $13 billion (18 percent). Other nonmanufacturing industries, a diverse group that includes mining, broadcasting, finance, insurance, and real estate, made up about $12 billion (17 percent) of R&D spending in the nonmanufacturing sector in 2001.

3. The R&D data for the trade sector contain some spending that might be more accurately associated with other industries. For instance, a significant number of computer and pharmaceutical manufacturers have more employees engaged in selling and distribution activities than in production or R&D activities. As a result, they are classified as a trade company rather than as a computer or pharmaceutical company, and all of their R&D investment is assigned to the trade industry. Although precise data are not available, supporting information from the National Science Foundation suggests that about three-quarters of the R&D classified as related to wholesale trade probably belongs in the computer and pharmaceutical categories.

Figure 2.

Federal and Nonfederal Spending for R&D as a Share of GDP, 1953 to 2002

(Percentage of GDP)



Source: Congressional Budget Office based on data from the National Science Foundation.

Note: R&D = research and development; GDP = gross domestic product.

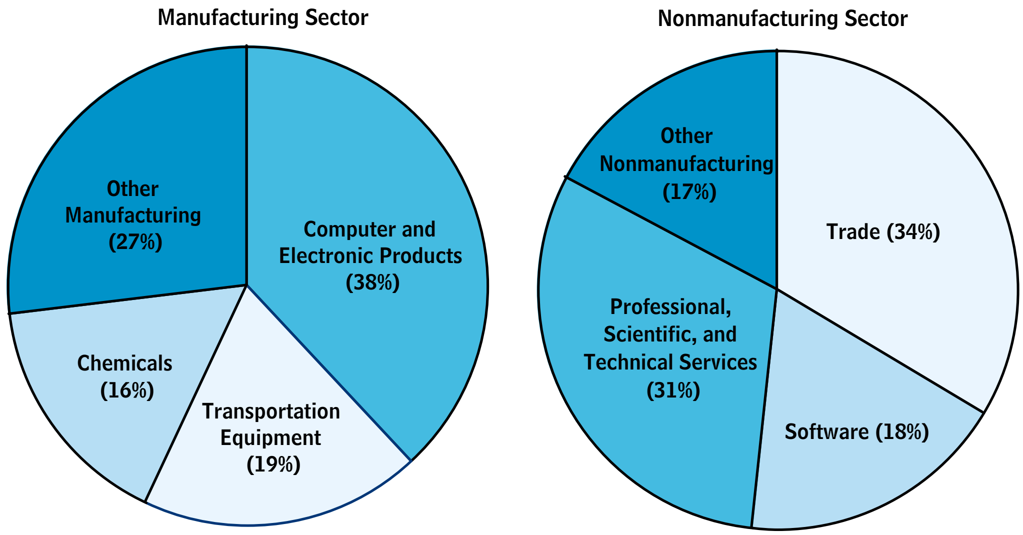
Estimating the Contribution That R&D Spending Makes to Productivity Growth

To estimate the impact of R&D spending on productivity growth, most researchers use econometric analysis, which includes a variety of statistical techniques for examining the relationship between economic variables. Specifically, analysts have used regression equations to estimate the effects of changes in R&D on such variables as production costs, output, and productivity, using data for individual firms, industries, or entire economies. If satisfactory equations were found, they could provide estimates of the R&D parameters that might be used in CBO's models of the economy.

Most econometric studies can be divided into two categories: those that estimate the effect of R&D spending on output or productivity (production function studies) and those that estimate the effect on production costs (cost function studies). The two approaches are related—it is possible to derive a cost function from a production function, and vice versa—but they use different statistical methods and have different data requirements. Studies that use the production function approach, which are more prevalent in the empirical literature, have at least two variants: cross-sectional studies, which examine the levels of variables in different firms or industries at a single point in time; and time-series studies, which consider changes in variables over time. The results from econometric studies that are most relevant for CBO's long-run models are those based on time-series data at the economywide level, because that is how the equations in CBO's models are specified.

Figure 3.

Private R&D by Sector, 2001



Source: Congressional Budget Office based on data from the National Science Foundation.

The strand of the empirical literature on R&D that includes case studies and cost-benefit analyses will not be reviewed in this paper. Those kinds of studies have the advantage of analyzing a specific type of R&D in considerable depth. However, they are not addressed here because of their principal disadvantage: their results are hard to generalize because their authors tend to select projects that turn out to be successful. Unlike case studies, econometric studies incorporate all R&D projects in their estimates of R&D expenditures or the R&D stock, regardless of whether the projects are successful. Thus, if those expenditures do not generate financial benefits but are nevertheless included in overall R&D, econometric studies will show a lower rate of return than if those expenditures had been omitted. As a result, such studies provide overall quantitative results, although they lack some detail.

The Theoretical Framework

The starting point for most econometric studies of the contribution of R&D to productivity growth is a production function—a mathematical equation that describes how labor, capital, and other factor inputs are combined to produce output. A Cobb-Douglas production function is a common choice:

$$(1) \quad Q_t = Ae^{\lambda t}K^{\alpha}_{t-1}L^{\beta}_{t}R^{\gamma}_{t-1}e^{\varepsilon}$$

where Q = real output,

A = total factor productivity (TFP),

K = the stock of physical capital,

L = the labor input, and

R = a measure of R&D effort.

The precise definitions of the variables in the production function differ depending on the study. For example, studies that use aggregated data typically use real GDP as their measure of

output, whereas studies that use firm-level data tend to use firms' revenues. Similarly, the preferred measure of labor input is hours worked, but some researchers use number of people employed if hours are unavailable. The stock of physical capital is an estimate of the total amount of productive assets (for example, structures and equipment) available to a firm, an industry, or an economy (depending on the coverage of the study). The R&D variable can be measured as the stock of R&D capital (which is calculated by cumulating net R&D investment over several years) or the investment in R&D in a given year. The subscript t-1 on the physical capital and R&D variables indicates that they often enter the production function as lagged values. The TFP measure—output per unit of combined factor input—is typically estimated as a time trend or a constant in the regression equation (see Griliches, 1979, for details).

Equation (1) can be rewritten in logs as

$$(2) \qquad \log(Q_t) = \log(A) + \lambda t + \alpha\log(K_{t-1}) + \beta\log(L_t) + \gamma\log(R_{t-1}) + \varepsilon_t .$$

Some studies estimate regressions based on equation (2) by using time-series data, meaning that they have data for a series of years for an industry or an economy. Known as time-series studies, such efforts gauge the effect on output of changes in the variables on the right-hand side of the equation, such as R&D. Other studies estimate equations such as equation (2) by using data for individual firms at a given point in time. Referred to as cross-sectional estimates, those studies indicate whether firms that undertake more R&D have higher levels of output (or productivity) than firms that undertake less R&D.

By taking first differences, equation (2) can be expressed in terms of growth rates, or

$$(3) \qquad (\Delta Q_t / Q_{t-1}) = \lambda + \alpha(\Delta K_{t-1} / K_{t-2}) + \beta(\Delta L_t / L_{t-1}) + \gamma(\Delta R_{t-1} / R_{t-2}) + \Delta\varepsilon_t$$

where the growth rates in the equation can be year-to-year changes or average growth rates spanning a period of several years and the parameters α, β, and γ are the elasticities of output with respect to physical capital, labor, and R&D, respectively. (An output elasticity is an estimate of the percentage increase in output that would result from a 1 percent increase in one of the factor inputs.) Of course, researchers are most interested in γ, the elasticity associated with R&D effort; they want to know both its magnitude and whether it is statistically significant.

The principal advantage of estimating equations such as (2) and (3) is their simplicity. Those equations require very few assumptions about the production function, demand relatively little data, and provide results that have a straightforward interpretation. For example, the coefficient on the R&D variable γ measures the elasticity of output with respect to R&D effort. That is, it represents the percentage change in output that is associated with a 1 percent change in R&D effort, as measured by the R&D variable. If γ equals 0.20, for example, then a 10 percent increase in the R&D stock would be associated with a 2 percent increase in output, all else being equal.

The main disadvantage of equations such as (2) and (3) is the likelihood that the estimated parameters will be biased because the assumptions required by the ordinary least squares (OLS) approach—a common method of statistical analysis—are not satisfied. For cross-sectional estimates, bias is likely to be present because of omitted variables. That is, if some firms

are more productive than others for reasons unrelated to R&D and those firms spend more money on R&D (perhaps because they are successful), then there will be differences in the levels of output or productivity that are correlated with R&D, and those differences will bias upward the estimated coefficient on R&D spending.

A similar problem can occur in studies that use time-series data. Termed simultaneity bias, that issue arises when one or more of the explanatory variables in a regression equation are correlated with the equation's error term, in violation of the OLS assumption that they be independent. That assumption is satisfied when the flow of causality runs in one direction, from the explanatory variables to the dependent variable. R&D investment and productivity, by contrast, are likely to be mutually dependent—growth of output is a function of, among other things, R&D investment, and R&D investment is a function of past output growth and expected future output growth. If that is so, any unobserved shock to productivity that raises output could indirectly raise investment in R&D, inducing a correlation between an explanatory variable (the R&D stock) and the error term in the productivity equation. Under those circumstances, output and capital are determined simultaneously, and OLS-based estimates of the coefficient on R&D will be biased. Several statistical techniques are available to solve the simultaneity problem, but they are not always applied to the R&D question because the data required to use them do not always exist.[4]

Another problem associated with time-series estimates of production functions in general and with the impact of R&D in particular is multicollinearity, which occurs when a linear relationship exists among the independent variables in a regression equation. If the linear relationship is perfect, it will be impossible to estimate the equation using the OLS approach. More commonly, there is a correlation among the independent variables, meaning that they move together but not in lockstep. In that situation, the OLS method does not have enough independent variation in the colinear variables to allow analysts to calculate with confidence the separate effect on the dependent variable of each colinear variable. As a result, the estimates of the parameters are imprecise—they tend to have large estimated variances and little statistical significance.

One final problem with estimates based on equation (2) or (3) is that those equations implicitly assume that the elasticity of output with respect to R&D (γ) is constant through time (or across firms). Some authors have objected to that assumption and have chosen instead to use an equation that yields an estimate of the rate of return to R&D instead of the R&D elasticity. (The rate of return to R&D is defined as the increment to output or TFP that would result from an increase of $1 in the R&D stock.) Such equations assume that the rate of return to R&D is constant over time or among firms; they take the following form:

$$(4) \qquad (\Delta Q_t / Q_{t-1}) = \lambda + \alpha(\Delta K_{t-1} / K_{t-2}) + \beta(\Delta L_t / L_{t-1}) + \rho(\Delta R_t / Q_t) + \Delta\varepsilon_t$$

where ΔR = net investment in R&D capital, and
ρ = the rate of return to R&D.

Equation (4) expresses output growth as a function of the rates of growth of labor and capital, along with the simple change in the R&D stock as a ratio to output (sometimes referred to as

4. Those methods include indirect least squares, two- and three-stage least squares, instrumental variable estimation, and maximum likelihood estimation.

R&D intensity).[5] Since the change in the R&D stock is equivalent to net investment in R&D, researchers can use the R&D spending-to-output ratio as their measure of R&D intensity, thus avoiding the need to calculate an R&D stock. Equation (4) can be estimated by using either cross-sectional or time-series data at any level of aggregation (firm, industry, or economywide) to determine the value of ρ, the rate of return to R&D capital.

If the production function has constant returns to scale, then equation (4) can be rewritten in terms of TFP (or labor productivity) as

$$(5) \quad (\Delta TFP_t / TFP_{t-1}) = \lambda + \rho(\Delta R_t / Q_t) + \Delta\varepsilon_t .$$

Instead of a single step to estimate the relationship between output and R&D (and other variables), two steps are required when the TFP equation is used. First, one must calculate TFP, implicitly imposing constant returns to scale on the production function. Second, one must estimate a regression by using TFP on the left-hand side of equation (5).

The advantages of studies that estimate the rate of return to R&D mirror those that estimate the elasticity of R&D: they include ease of interpretation and a minimum of extra restrictions on the functional form. Added advantages of the TFP studies are that the R&D intensity is observable (the researcher does not need to estimate the stock of R&D capital) and that such studies avoid the need to estimate the output elasticities of labor and physical capital.

Nevertheless, there are some disadvantages to the approach taken by the TFP studies. First, that method makes the estimate of the rate of return to R&D sensitive to the exact definition of the variable that is measuring R&D intensity. In particular, it matters whether R&D intensity is measured as a ratio of R&D spending to sales or to value added. Second, the estimate of the rate of return also varies according to whether the variables in the regression are corrected for double counting of the R&D inputs—in other words, whether the labor and capital used to produce R&D are removed from the labor and capital inputs in the production function. Third, the estimate of the return to R&D is also sensitive to the assumed rate of depreciation. The rates of return in equations such as equation (5) are gross rates, meaning that they include depreciation. Most rates of return—for example, the rate of return to physical capital—are expressed as net rates; that is, depreciation is subtracted from them. Estimates of R&D depreciation—which may be as much as 15 percent—are surprisingly high, given that knowledge does not deteriorate in the same way that physical capital does.[6]

5. To derive equation (4), note that the elasticity of output with respect to R&D is defined as

$$\gamma = (\partial Q / \partial R) \bullet (R/Q) \text{ (time subscripts have been omitted for simplicity).}$$

The derivative on the right-hand side of the equation, $(\partial Q/\partial R)$, is the rate of return to R&D (ρ). Substituting that definition of the R&D elasticity in equation (3) yields

$$\Delta Q/Q = \lambda + \alpha(\Delta K/K) + \beta(\Delta L/L) + (\partial Q/\partial R) \bullet (\Delta R/Q) + \Delta\varepsilon_t ,$$

which when simplified becomes equation (4). For more details, see Griliches (1980), Griliches and Mairesse (1984), and Mairesse and Sassenou (1991).

6. For more discussion of depreciation, see Griliches and Mairesse (1984) or Mairesse and Sassenou (1991).

Cost functions are similar to production functions in that they treat the R&D stock as a factor of production that is similar to other factors such as labor and physical capital. However, instead of estimating the relationship between R&D and output, cost functions explore the link between R&D and production costs to determine whether R&D investments lower those costs. Typically, a cost function will relate the costs of production to the level of output and the relative prices of factor inputs, including variable factors (such as labor and materials) as well as fixed factors (such as physical capital and R&D). If successful R&D projects lower the costs of production, then the estimated coefficient on R&D in a cost function will be statistically significant. Although cost functions are equivalent to production functions in theory, in practice they are more complex and are typically estimated along with factor demand as part of a full system of equations. As a result, they require more-restrictive assumptions about the form of the estimating equations as well as more data.[7]

Studies that use cost functions employ a wider variety of functional forms than do production function studies, and they generally impose more structure on the estimated system. Although the cost function approach poses the risk of misspecification, it also increases the statistical efficiency of the estimated system and allows researchers to use shorter time series or more finely disaggregated data without resorting to such expedients as pooling or the imposition of common parameters. Cost functions also permit R&D to interact with other factor inputs—in order to determine, for example, whether R&D spending increases the demand for other inputs; in addition, they can allow for the possibility of different adjustment costs among inputs (meaning the ease with which firms can vary the levels of the various inputs). Moreover, cost function estimates are less subject to the problem of multicollinearity that is common to time-series estimates of production functions.

The drawbacks associated with the use of cost functions center on their use of output and input prices as explanatory variables on the right-hand side of the estimating equation. All explanatory variables are assumed to be exogenous, a dubious assumption for output; if that assumption was not true, it could lead to biased estimates of parameters. Input prices are more likely to be exogenous, but it is hard to find good data on input prices that differ across firms and over time, especially for factors such as capital and R&D. That limitation is important because most of the statistical results from cost function studies are driven by variation in input prices. Moreover, expected input prices and output should be used rather than actual values. The use of actual output could produce unwarranted evidence of economies of scale and might bias upward the estimates of the coefficients on R&D capital—especially in the absence of any other trend terms in the equations.

Measurement Issues in Empirical Studies of R&D and Productivity

Regardless of what functional form or estimating technique is used to gauge the contribution of R&D to productivity growth, certain measurement issues arise in all empirical studies of R&D. Those issues center on the data used to measure innovation and the products of such efforts. Although a variety of data are available, including R&D spending, rates of patenting, and spending for equipment that embodies technological advances, most of the measures

7. The arguments in this paragraph and the two that follow are based on discussions in Griliches (1992, 1995), Mohnen (1992), and Australian Industry Commission (1995).

of R&D input and output are indirect and only imperfectly reflect the contribution of innovation.[8]

Issues Associated with Measuring Output. To estimate the contribution of R&D to the growth of productivity, analysts must be able to measure the increase in output of a firm, industry, or sector that arises from a boost in R&D spending. That task is difficult because the fundamental product of R&D effort is an improvement in quality—the goal of R&D is to make existing goods and services better or to invent entirely new products. Capturing those improvements in quality is a challenge for government agencies that gather the data underlying the national income and product accounts (NIPAs).

The solution to that problem is the use of price indexes that reflect the improvements in quality that are embedded in new or newly improved goods. When those so-called hedonic price indexes are used, increases in quality show up in the NIPAs as smaller hikes in prices (or outright declines). As a result, more of a given increase in nominal sales will be classified as an increase in real output rather than as an increase in price, and the rate of productivity growth will be higher. Industries marked by innovation and rapid increases in quality (computers and microprocessors are prime examples) have shown faster productivity growth as statistical agencies have replaced regular price indexes with hedonic indexes.

The use of hedonic price indexes in the NIPAs has increased substantially during the past 20 years, and components of GDP that are deflated by hedonic techniques account for roughly one-fifth of gross domestic product (see Moulton, 2001). One notable gap in the coverage, however, is the output of service industries, which is difficult to measure in inflation-adjusted terms—and even more difficult to measure in quality-adjusted terms. Casual inspection reveals that technological innovation, especially in the area of information technology, has transformed the way that many service industries operate. Banks, brokerages, airlines, and hospitals all do business more efficiently than in the past. Yet that improvement has not been fully reflected in measurements of the real output of those industries.

When the output of some but not all industries is adjusted for quality, the possibility arises that the gains from R&D that are attributed to one industry actually originate in a different industry. A likely scenario is a case in which the output of one industry is adjusted for quality but the output of the industries that supply inputs to it are not. Consider the example of personal computers, which have rapidly improved in quality since they were first introduced. Much of that improvement, however, arose because the components used to assemble computers improved: the speed of microprocessors increased, the capacity of disk drives expanded, and the picture quality of video displays improved. If the price of a personal computer was adjusted for improvements in quality but the prices of the various components were not, then some of the productivity of companies producing components such as microprocessors would show up in the NIPAs as the productivity of computer firms. The gains from R&D in the

8. The Bureau of Economic Analysis (BEA) is exploring the idea of adding R&D expenditures and capital to the national income and product accounts. As a first step, BEA has produced a set of satellite, or supplemental, accounts (see Fraumeni and Okubo, 2002).

microprocessor industry, for example, might be misattributed to the personal computer industry.[9] That kind of misattribution describes what happened when hedonics were first used for computers.

Computing the output of individual firms by deflating each firm's sales by a common (industrywide) price index raises another measurement issue. Virtually all of the firm-level studies of the link between R&D and productivity use that approach, deflating each firm's revenues by an industrywide or economywide price index. Although that method is usually the only alternative—data on individual firms' prices being unavailable—it is likely to yield both a misleading estimate of firm-level productivity and biased estimates of parameters when used in a regression equation to estimate a production function.[10]

Issues Associated with Measuring R&D Capital. To measure the return to R&D, researchers need a measure of R&D effort, a difficult proposition because R&D is such an amorphous concept. Researchers usually measure that effort by using an estimate of R&D capital, which is calculated by cumulating past R&D investments (with an appropriate deduction for depreciation). However, R&D capital, unlike physical capital, does not exist in tangible form, even though it can be embodied in such items as blueprints and technical manuals. Instead, R&D capital is a body of knowledge that grows in myriad ways—through schooling, on-the-job training, conferences, and research. Aggregating such a diverse set of activities into a single measure of R&D capital is a daunting task made more complicated by the fact that knowledge has no market counterpart—the components that need to be aggregated are rarely bought and sold in traditional markets. And of course, measured R&D spending represents only a small subset of the ways in which new ideas are formed. Researchers focus on it because spending data are available.

The first issue associated with measuring R&D capital is the delay between the time an R&D project is undertaken and the point at which it might contribute to production. That lag can arise from many sources; research projects may take months or even years to complete. Once a project is finished, assuming it is successful, the firm must decide whether to use its results, either by producing a new good or improving an existing one. After the idea has been implemented, there may be another delay before revenues begin to flow in. In sum, the time between a given expenditure for R&D and its effect on productivity can be considerable. Careful estimation of the dynamic effects of R&D requires a long time series of R&D expenditures that is often unavailable.

Second, researchers must confront the issue of depreciation, or obsolescence. The end result of R&D investments, knowledge, does not deteriorate with age in the same manner that other capital assets do. However, the private return to a firm that develops a new idea, product, or process (that is, the gain in revenues that accrues to a firm as a result of R&D spending) will diminish through time because other firms will eventually imitate the original innovation or

9. Rapid technological change in the computer sector provides a vivid example of the productivity payoff from R&D, at least at the sectoral level. A number of studies examine the contribution to overall productivity growth made by information technology industries; they include work by Jorgenson and Stiroh (2000) and Oliner and Sichel (2000). However, in that literature, the return to R&D is not estimated, so those studies are not examined in this paper.

10. That argument has been made by Klette and Griliches (1996) and Katayama, Lu, and Tybout (2003).

because better ideas and products will be invented and will supplant it. For example, the knowledge required to make steam-powered locomotives—a major innovation during the 19th century—still exists, but few are manufactured because they have been replaced by better transportation technologies.

A third issue associated with R&D capital is the potential for inconsistency among the variables used in regression equations to estimate the impact of R&D spending. Most studies in that literature fail to remove from their labor and capital inputs the labor and physical capital used to produce R&D. That practice has the effect of double counting the R&D labor and physical capital—once in the measure of R&D capital and again in the traditional measures of labor and physical capital.[11]

Finally, there is the question of spillovers. Firms produce goods and services using labor, capital, and knowledge derived from their own R&D activities. In addition, firms benefit in many cases from R&D undertaken by other firms in the same industry or by firms in other industries or other countries, as well as from basic research performed in academic settings. To estimate the effect of "outside" knowledge on the productivity of a given firm is a challenge. That impact will depend on many factors, none of which is easy to measure, including the geographic proximity of the originating and receiving firms and the similarities between their production processes. Presumably, the ability of firms to take advantage of innovations that originate elsewhere has increased since the advent of the Internet.

Note that one of the measurement problems discussed earlier can make it appear that spillovers exist when in fact they do not. That situation could arise if the quality improvements in the output of an R&D-intensive industry were not measured by the price indexes for that industry and if that industry's output was an input to production in a second industry. In that case, the higher-quality input would raise productivity in the second industry, apparently through a spillover from the R&D effort of the first industry. In fact, though, the R&D effort would actually raise productivity in the first industry (in the form of a higher-quality product), but that increase would not be measured in the statistics.

Econometric Estimates of R&D's Contribution to Productivity Growth

Econometric studies provide the evidence that is most relevant to the questions asked in the introduction to this paper: does R&D, as measured, contribute to productivity growth, and if so, can the estimate of that contribution be pinned down so that R&D can be added to existing models of long-run growth? Most empirical studies estimate the private return to R&D; they use either cross-sectional or time-series data at various levels of aggregation, although most concentrate on the firm or industry level. Many of the more recent studies have focused on the social return to R&D, which is defined as the total return to innovation, including the return earned by the original innovator and any gains that spill over to other firms not involved in the R&D effort. Thus, noninnovating firms may benefit from the knowledge embodied in the original innovation.

11. That argument originated with Schankerman (1981) and has been echoed by Cuneo and Mairesse (1984) and Griliches and Mairesse (1984).

Estimates of the Private Return to R&D

The core of the empirical literature on R&D comprises studies that estimate the private return to R&D by using data at the firm or industry level, and their results, though not uniform, are the most consistent across studies. They seem to form the basis for the consensus that the elasticity of R&D is positive and significant (that is, it differs significantly from zero), with a central tendency between 0.10 and 0.20. Among such studies, those that employ time-series data show weaker results, with smaller coefficients and less statistical significance, than those that use cross-sectional data.

Fewer studies estimate the impact of R&D spending on productivity by using economywide data, and those that do suggest a weaker effect of R&D on productivity. Results are also less uniform: estimates of the R&D elasticity span a wide range (from zero to 0.60) and are often insignificant. A key question for users of macroeconomic models is whether it is possible to reconcile the results of studies that use micro-level data with those that use macro-level data.

Estimates from Studies That Use Firm- or Industry-Level Data. The earliest research to investigate the effects of R&D on productivity centered on individual industries within manufacturing and especially on the agricultural sector.[12] Those sectors attracted researchers because they had clearly defined output and relatively good data associated with them. The studies used cross-sectional data and generally found that R&D had a positive and significant effect on productivity growth in the sector being examined. As time passed and more sources of data became available, later studies tended to broaden the samples by including more industries, many firms in a single industry, or many firms in many industries.[13] A common thread is the studies' continuing focus on the manufacturing sector, typically with the use of cross-sectional data in an equation such as equation (2) above. Those later studies generally confirmed the role of R&D as a significant contributor to differences in productivity levels among firms.

Cross-sectional estimates are based primarily on the information provided by the individual differences among firms in the levels of variables. By comparison, time-series estimates relate to the changes in variables through time within individual firms. The cross-sectional category also includes studies that analyze how companies differ in the growth rates of variables—that is, companies that grew faster during the sample period, that had faster growth of R&D, or, more typically, that had higher levels of R&D spending or stocks.

Estimates of the R&D elasticity γ from those studies vary on the basis of the sample: they range from about 0.05 to 0.60 for studies that used data for individual firms and from zero to 0.50 for studies that used data for industries or sectors (see Table 1). Despite the wide range of estimates, the central tendency runs from about 0.10 to about 0.20.[14] Moreover, the elasticity estimates are, by and large, statistically significant. Those estimates imply that within an industry, companies that have more R&D capital (or greater R&D intensity) have higher levels of productivity than otherwise similar firms.

12. Studies in that literature include Mansfield (1965), Minasian (1969), and Griliches (1973).

13. Examples include Terleckyj (1974), Griliches (1980b, 1986), Mansfield (1980), Schankerman (1981), Cuneo and Mairesse (1984), Griliches and Mairesse (1984), and Jaffe (1986).

14. That central tendency, which is cited frequently, comes from Griliches (1988). See also Mairesse and Sassenou (1991) and Australian Industry Commission (1995).

Table 1.

Selected Estimates of the Elasticity of Private R&D from Cross-Sectional Studies

Study	R&D Elasticity[a]	Sample
Minasian (1969)	0.11 - 0.26	17 U.S. firms (chemical industry); 1948 to 1957
Griliches (1980a)	0.03 - 0.07	39 U.S. manufacturing industries; 1959 to 1977
Griliches (1980b)	0.07	883 U.S. firms, 1957 to 1965
Schankerman (1981)	0.10 - 0.16	110 U.S. firms (chemical and oil industries); 1963 cross-section
Sveikauskas and Sveikauskas (1982)	0.22 - 0.25	144 U.S. manufacturing industries; 1959 to 1969
Cuneo and Mairesse (1984)	0.20	182 French manufacturing firms; 1972 to 1977
Subsample 1	0.21	98 firms in scientific sectors
Subsample 2	0.11	84 firms in nonscientific sectors
Griliches and Mairesse (1984)		
Sample 1	0.05	133 U.S. firms; 1966 to 1977
Sample 2	0.19	77 U.S. firms (scientific sectors); 1966 to 1977
Griliches (1986)		491 U.S. firms
Subsample 1	0.11	1972 cross-section
Subsample 2	0.09	1977 cross-section
Jaffe (1986)	0.20	432 U.S. firms; 1973 and 1979
Englander, Evenson, and Hanazaki (1988)	(0.16) - 0.50	16 industries across six countries; 1970 to 1983
Mansfield (1988)	0.42	17 Japanese manufacturing industries
Griliches and Mairesse (1990)		
Sample 1	0.25 - 0.41	525 U.S. manufacturing firms; 1973 to 1980
Sample 2	0.20 - 0.56	406 Japanese manufacturing firms; 1973 to 1980
Hall and Mairesse (1995)	0.05 - 0.25	197 French firms; 1980 to 1987
Wang and Tsai (2003)	0.19	136 Taiwanese manufacturing firms; 1994 to 2000

Source: Congressional Budget Office based on Mairesse and Sassenou (1991), Mohnen (1992), and Australian Industry Commission (1995).

Note: R&D = research and development.

a. Parentheses indicate negative numbers.

When researchers move from an equation such as equation (2) to one such as equation (3), meaning that they switch from cross-sectional data to time-series data, a different picture emerges. Estimates of the elasticity of R&D (and the elasticity of physical capital) from studies that use time-series data are generally much lower than those obtained from studies using cross-sectional data (see Table 2). Indeed, with few exceptions, estimates of the R&D elasticity that are derived from time-series studies lose their statistical significance.[15] In a statistical sense, that result is not surprising: the R&D data have much more variation in the cross-sectional dimension than in the time-series dimension. If that result is valid, it suggests that companies that invest more in R&D have higher levels of productivity than those that invest less—but the relationship might not be causal. Some other factor that is correlated with both R&D and output may be raising the productivity of the R&D-intensive firms. In that case, an increase in R&D spending by a given firm might not lead to an increase in productivity. Similarly, policies to boost the R&D share of GDP might not speed the growth of productivity at the economywide level.

A 1995 study by Bronwyn Hall and Jacques Mairesse is a good example of an empirical study of the link between R&D and productivity because its data, methods, and results are typical of studies in that literature.[16] The authors estimate equations such as equations (2) and (3) by using data from a sample of French manufacturing firms for the 1980-1987 period to estimate the R&D elasticity γ and to determine how that result responds to changes in underlying assumptions (such as constant returns to scale in the production function, the depreciation rate used to compute the R&D capital stock, and the choice of whether to include an adjustment for double counting of R&D expenditures in the labor and capital inputs).

Hall's and Mairesse's findings are also representative of the results from this literature. Using cross-sectional data in equation (2), the authors found that the R&D elasticity was positive, ranging from about 0.20 to 0.25, and strongly significant, with *t*-statistics that exceeded 30. However, when they reestimated the equation using time-series data, the estimate of the elasticity fell sharply, and the statistical significance nearly vanished. When they estimated the equation using data expressed in levels, the elasticity ranged from essentially zero to 0.07 (depending on the assumptions used) and was either insignificant or barely significant. When the equations were estimated using growth rates, the R&D elasticity ranged from 0.02 to 0.05 and was statistically insignificant. Moreover, the time-series estimates suggested other counterintuitive results, including a negative coefficient on the labor input and a low estimate of the elasticity of physical capital.

Hall's and Mairesse's summing up of their empirical results could well describe the entire literature:

> *[T]he pattern of estimates usually yields an R&D capital elasticity in the cross-section dimension which is statistically significant, usually large, and even possibly of the same order of magnitude as the elasticity of ordinary capital, whereas the estimates in the time*

15. See Mairesse and Sassenou (1991), Australian Industry Commission (1995), and Hall and Mairesse (1995).

16. The Hall and Mairesse paper updates a series of studies on R&D and productivity that uses data from the 1970s, including Griliches and Mairesse (1983, 1984) and Cuneo and Mairesse (1984).

Table 2.

Selected Estimates of the Elasticity of Private R&D from Time-Series Studies

Study	R&D Elasticity[a]	Sample
Minasian (1969)	0.08	17 U.S. firms; 1948 to 1957
Griliches (1980b)	0.08	883 U.S. firms; 1957 to 1965
Cuneo and Mairesse (1984)	0.05	182 French manufacturing firms; 1972 to 1977
Subsample 1	0.14	98 firms in scientific sectors
Subsample 2	0.03	84 firms in nonscientific sectors
Griliches and Lichtenberg (1984b)	(0.04)	27 U.S. manufacturing industries; 1959 to 1976
Griliches and Mairesse (1984)	0.09	133 U.S. firms; 1966 to 1977
Griliches (1986)	0.12	652 U.S. firms; 1966 to 1977
Jaffe (1986)	0.10	432 U.S. firms; 1973 and 1979
Bernstein (1988)	0.12	7 Canadian manufacturing industries; 1978 to 1981
Hall and Mairesse (1995)	0 - 0.07	197 French firms; 1980 to 1987
Verspagen (1995)	(0.02) - 0.17	14 industries in 11 OECD countries; 1973 to 1988

Source: Congressional Budget Office based on Mairesse and Sassenou (1991), Mohnen (1992), and Australian Industry Commission (1995).

Note: R&D = research and development; OECD = Organization for Economic Cooperation and Development.

a. Parentheses indicate negative numbers.

> *dimension, which control for permanent differences across firms, whether within, long-differenced, or first-differenced, typically have an R&D capital elasticity which is much smaller, about one-third or half that of ordinary capital, and often statistically significant (p. 277).*

That assessment echoes the conclusion of an influential survey of the R&D literature by Mairesse and Mohamed Sassenou, who assert that "the time-series estimates of the R&D elasticity γ, as well as the estimates of the physical capital elasticity α, generally tend to be lower than the corresponding cross-sectional estimates" (Mairesse and Sassenou, 1991, p. 13). The authors go on to say that the phenomenon may be attenuated by either constraining the labor elasticity to equal its share in national income or by imposing constant returns to scale (that is, enforcing that the sum of the coefficients on the factor inputs equals one). When Hall and Mairesse impose the assumption of constant returns to scale, the coefficient on R&D regains its significance in some but not all of their time-series specifications.

Like the estimates of the R&D elasticity, estimates of the rate of return to R&D from TFP equations such as equation (5) span a very wide range, depending on the type of data, estimating method, and degree of aggregation. The range of estimates of the rate of return to R&D runs from zero to nearly 0.60, with a central tendency between 0.20 and 0.30 (see Table 3).

Table 3.

Selected Estimates of the Rate of Return to Private R&D

Study	Rate of Return to R&D[a]	Sample
Terleckyj (1974)	0 - 0.30	33 U.S. industries; 1948 to 1966
Mansfield (1980)	0.27	16 U.S. firms (chemical and petroleum industries); 1960 to 1976
Terleckyj (1980)	0.20 - 0.27	20 U.S. manufacturing industries; 1948 to 1966
Link (1981b)		
Subsample 1	0	174 U.S. firms; 1971 to 1976
Subsample 2	0.07	33 U.S. firms (chemical industry); 1971 to 1976
Scherer (1982)	0.13 - 0.29	87 U.S. manufacturing industries; 1964 to 1969 and 1973 to 1978
Griliches and Mairesse (1983)		
Regular sample	0.28	528 U.S. and French firms; 1973 to 1978[b]
Industry dummies	0.12	528 U.S. and French firms; 1973 to 1978[b]
Odagiri (1983)		
Subsample 1	0.26	123 Japanese firms (scientific sectors); 1969 to 1981
Subsample 2	(0.47)	247 Japanese firms (other sectors); 1969 to 1981
Clark and Griliches (1984)	0.20	924 U.S. manufacturing plants; 1970 to 1980
Griliches and Lichtenberg (1984a)	0.04 - 0.30	193 U.S. manufacturing industries; 1959 to 1978
Odagiri and Iwata (1986)		
Regular sample	0.20	135 Japanese firms; 1966 to 1973
Industry dummies	0.17	135 Japanese firms; 1966 to 1973
Odagiri and Iwata (1986)		
Regular sample	0.17	168 Japanese firms; 1974 to 1982
Industry dummies	0.11	168 Japanese firms; 1974 to 1982
Mansfield (1988)	0.42	17 Japanese industries; 1960 to 1979
Goto and Suzuki (1989)	0.22 - 0.56	40 Japanese manufacturing firms; 1976 to 1984
Sterlacchini (1989)	0.10 - 0.30	15 U.K. manufacturing industries; 1954 to 1984
Lichtenberg and Siegel (1991)	0.13	2,207 U.S. firms; 1972 to 1985
Griliches (1994)	0.12 - 0.46	142 U.S. manufacturing industries; 1958 to 1989
Hall and Mairesse (1995)	0.06 - 0.34	197 French firms; 1980 to 1987
Jones and Williams (1998)	0.35	12 U.S. manufacturing industries; 1961 to 1989

Source: Congressional Budget Office based on Mairesse and Sassenou (1991), Mohnen (1992), and Australian Industry Commission (1995).

Note: R&D = research and development.

a. Parentheses indicate negative numbers.

b. The sample consisted of 343 U.S. firms and 185 French firms.

The wide variation in the estimates probably arises from subtle differences among studies in the data they used or in their specification of the TFP equation.[17]

Although related, the estimates of the rate of return to R&D in Table 3 are not directly comparable with the elasticity estimates in Tables 1 and 2. Recall that the rate of return measures the change in output caused by an increase of $1 in the R&D stock, whereas the elasticity measures the percentage increase in output that results from a 1 percent increase in the stock. It is not always possible to compute the R&D elasticity from the rate of return (and vice versa) because the relationship depends in part on the estimate of the R&D stock, which differs among studies.

Although not directly comparable, the estimates of the rate of return to R&D derived from TFP equations share an important characteristic with the estimates of the R&D elasticity. Most of the information that is used to determine the coefficient on R&D intensity comes from the cross-sectional dimension, even though the equations are estimated by using TFP growth. Charles Jones and Jeffrey Williams demonstrated that property in a 1998 study in which they estimated a TFP equation that was meant to replicate the results typically found in the literature. Their equation yielded a statistically significant estimate of 0.35 for the rate of return to R&D when it was freely estimated. However, when they used dummy variables to remove the influence of differences among industries in the estimated rate of return, the statistical significance of the R&D variable disappeared. By contrast, when they removed the influence of changes through time in their explanatory variables, the estimated coefficients showed little change.

The results from the studies that use cost functions are similar to the estimates of the rate of return from the TFP studies. Although fewer in number, the cost function studies suggest that the return to R&D, which is generally in the 0.20 to 0.25 range, is higher than the return to physical capital and is also subject to greater variability. The studies that this literature encompasses generally find that physical capital and R&D capital are complements rather than substitutes and that industries that receive a higher return to physical capital tend to receive a higher return to R&D as well.[18]

One notable result that is common to all of the separate strands of the empirical literature cited above is that industries differ substantially in the return they receive from R&D. Those disparities are much greater than the differences among firms in the same industry or the differences among the same industries in different countries. Introducing dummy variables to control for differences among industries in the TFP regressions, for example, generally trims the estimated rate of return to R&D and reduces its significance. Moreover, several studies have found that R&D performed in "scientific" or "research-intensive" industries (such as chemicals, pharmaceuticals, computers, and electronics) produces bigger returns than R&D

17. For example, studies differ in the dependent variable they use (labor productivity or TFP) and how it is calculated (using different estimates of the income shares) and in whether the data are corrected for double counting of R&D inputs. For more details, see Mairesse and Sassenou (1991, p. 18) or Australian Industry Commission (1995, p. QA-36).

18. The discussion in this paragraph is based on Mohnen (1992) and Australian Industry Commission (1995).

carried out in other manufacturing sectors.[19] Although the elasticity of R&D is generally positive and significant for scientific firms, it is generally smaller and often statistically insignificant for nonscientific firms. The same is true for the rate of return to R&D investment.

That result may be an example of the measurement problem discussed earlier—that the output of scientifically oriented industries may be easier to measure than the output of other industries. In other words, all sectors may experience positive returns to R&D, but measurement difficulties may prevent researchers from identifying them. In his 1994 paper, Zvi Griliches starkly illustrates that possibility. Griliches ran a typical TFP regression using industry data for the 1978-1989 period and reported that the rate of return to R&D, which exceeded 0.30, was statistically significant. However, he noted that the computer industry was a notable outlier—it had a much higher ratio of R&D to output and much faster productivity growth during the sample period than other industries had. At the time, the computer sector was the only one with output that was computed by using quality-adjusted price deflators, and including that sector in the regression had an enormous impact on the estimated coefficients. When Griliches excluded the computer sector from his regression equation, the return to R&D fell to 0.12 and lost most of its statistical significance. Griliches argued that if the data for other industries were computed using quality-adjusted price indexes, the computer sector would be much less of an outlier because its productivity growth would be reduced and other sectors' growth would be enhanced.

Other findings in the empirical R&D literature include the following:

- Studies that are able to separate R&D spending into components have found that the payoff to basic research is greater than the return to applied R&D. That result is based on cross-sectional estimates: firms that devote a larger share of their R&D budget to basic research have higher levels of productivity than those that devote a smaller share. Why basic research should raise productivity more than applied research does is unclear, but Edwin Mansfield (1980) found a positive relationship between long-term research and productivity at the firm level—even after controlling for a firm's level of basic and applied R&D. Hence, he speculated that basic research was acting as a proxy for long-term R&D in regressions that did not include that variable.[20]

- Some studies have found that correcting for the possibility of double counting increases the size of the R&D elasticity. As noted earlier, R&D effort will be double counted if the number of researchers engaged in R&D and the amount of physical capital used for it are not subtracted from the labor and capital inputs in the production functions before

19. See Griliches (1980b); Odagiri (1983); Cuneo and Mairesse (1984); Griliches and Mairesse (1984); Englander, Evenson, and Hanazaki (1988); Hall (1993); Verspagen (1995); and Wang and Tsai (2003). Terleckyj (1974) found that R&D was significantly linked to productivity in manufacturing but not in nonmanufacturing industries. By contrast, Sveikauskas (1981) suggested that the effect of research intensity on productivity growth was not concentrated in those few industries in which technological opportunities were especially favorable.

20. See also Link (1981a) and Griliches (1986).

estimation. Other research, however, has found that the bias that results from double counting of inputs does not seem to be large.[21]

- The evidence is mixed on the question of whether the return to R&D has changed over time. Several studies have concluded that the R&D elasticity shrank during the 1970s and early 1980s, but another set of studies did not find evidence of a decline, and at least one study found that the rate of return to R&D fell from a value of about 0.10 during the 1960s to roughly zero during the 1970s before recovering to about 0.05 by the end of the 1980s.[22] In his 1994 article in the *American Economic Review*, Zvi Griliches argued that the apparent decline during the late 1970s reported by some researchers might have resulted from the oil-price shocks during the period, which hit R&D-intensive sectors (such as chemicals and petroleum refining) particularly hard. Griliches concluded that there was no strong evidence of a long-term decline in the elasticity over time.

- Academic research has been found to make significant contributions to commercial R&D. Several studies have demonstrated the link between university research and private innovation and performance. That link seems to be stronger for companies in close geographic proximity to universities and for smaller firms compared with larger firms.[23]

Estimates from Studies That Use Economywide Data. The studies summarized thus far used microeconomic data to estimate the contribution of R&D to economic growth. More relevant from a macroeconomic modeling perspective would be results derived from data at the sectoral or economywide level. Unfortunately, only a limited number of studies examine the significance of R&D at the national or international level.[24] Many studies use cross-sectional data at the national level to analyze the sources of economic growth, but they tend not to focus on R&D spending because the required data are unavailable. Time-series studies are also sparse, probably because significant results are hard to come by. Since the aggregate data on R&D expenditures in the United States do not display much variation over time, it is difficult for such data to explain much of the historical variation in output or productivity growth. The problem is exacerbated by the fact that the R&D series is correlated with the physical capital series, which limits the ability of regression equations to identify the separate effects of the two series on productivity growth.

Nevertheless, some studies that use economywide data have been published. Elasticities of R&D calculated from those studies are in the same range as or perhaps a bit larger than those from the micro-based estimates (see Table 4). The central tendency is near 0.10, but like the elasticities from the micro-based studies, they span a wide range, from roughly zero to more than 0.60.

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21. Studies by Schankerman (1981), Cuneo and Mairesse (1984), and Hall and Mairesse (1995) argue for a significant bias. However, the Australian Industry Commission (1995) and Verspagen (1995) maintain that the bias is small.

22. Studies that found evidence of a decline include Griliches (1980b, 1986); Griliches and Lichtenberg (1984b); Englander, Evenson, and Hanazaki (1988); and Nadiri and Prucha (1990). Studies that did not find evidence of a decline include Clark and Griliches (1984), Griliches and Lichtenberg (1984a), Griliches and Mairesse (1984), Bureau of Labor Statistics (1989), and Lichtenberg and Siegel (1991).

23. For further discussion, see Jaffe (1989); Acs, Audretsch, and Feldman (1992); Jaffe, Trajtenberg, and Henderson (1993); and Cohen (1995).

24. Much of the material in this section is based on Australian Industry Commission (1995).

Table 4.

Selected Estimates of the Elasticity of Private R&D from Studies Using Aggregate Data

Study	R&D Elasticity	Sample (Variable Studied)
Nadiri (1980)	0.06 - 0.10	United States (labor productivity); 1949 to 1978
Patel and Soete (1988)	0.61	United States (TFP); 1967 to 1985
Lichtenberg (1992)	0.07	98 countries (per capita output); 1960 to 1985
Coe and Moghadam (1993)	0.17	France (output); 1971 to 1991
Coe and Helpman (1995)	0.23	G7 countries (TFP);[a] 1971 to 1990
Coe and Helpman (1995)	0.08	Non-G7 OECD countries (TFP);[a] 1971 to 1990
Australian Industry Commission (1995)		
Subsample 1	0.02	Australia (TFP); 1975 to 1991
Subsample 2	0.14	Australia (output); 1975 to 1991

Source: Congressional Budget Office based on Mairesse and Sassenou (1991), Mohnen (1992), and Australian Industry Commission (1995).

Note: R&D = research and development; TFP = total factor productivity; OECD = Organization for Economic Cooperation and Development.

a. The G7 countries are Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

Results from the economywide studies seem to be sensitive to the estimating method used and to the countries that are included in the data sample. The study by the Australian Industry Commission (1995, pp. QB17-QB19), for example, illustrates that sensitivity. In that research, the authors used a typical TFP equation and aggregate data for Australia (expressed in levels) for the 1975-1991 period. Their first version of the equation, which was similar to equation (5), yielded an estimate of the elasticity of R&D of about 0.06; the coefficient was statistically significant. However, when they added a time trend to the equation, the estimated coefficient was cut to 0.02 and lost all of its significance. Those results demonstrate, first, the importance of taking account in the equation of other factors that influence productivity (which the authors acknowledged) and, second, how fragile such results can be.

The possibility that estimates are sensitive to the countries that are included in the sample is suggested by the results of two other studies. David Coe and Elhanan Helpman (1995) used a sample of countries from the Organization for Economic Cooperation and Development (OECD). For the non-G7 countries in their sample, the estimated elasticity was 0.08; the elasticity was 0.23 for the G7 countries.[25] P. Patel and L. Soete, in their 1988 paper, estimated separate R&D elasticities for eight industrialized countries that ranged from 0.26 for Canada to as high as 0.82 for the United Kingdom. Those authors were very cautious about their findings, noting that R&D did not seem to explain certain low-frequency movements in pro-

25. The G7 countries are Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

ductivity growth in the United Kingdom and Canada. They also provided a cautionary note that has wide applicability: "Econometric studies in this area need therefore to be interpreted and taken with a large measure of scepticism. They provide useful hints and indications of presumed econometric relationships, which are however largely obscured by the difficulties in approximating some of the most crucial concepts" (p. 162).

Estimates of the Social Return to R&D Investments

R&D capital—which is really technical knowledge—has certain properties that distinguish it from physical capital. First, technical knowledge is nonrival in consumption, which means that it can be used by an unlimited number of people at the same time. Second, it is at least partially nonexcludable, which means that the owner of an idea cannot completely prevent others from using it.[26] Those properties raise the possibility that R&D investments are subject to spillovers—that is, the effects of R&D spending may partly spill over to firms not involved in the actual creation of the knowledge. In other words, firms benefit not only from their own R&D efforts but also from R&D undertaken by other firms in their industry and possibly from technical knowledge created anywhere in the world.

Spillovers can take many forms. Most commonly, they occur among firms in the same industry, perhaps as companies imitate their competitors or improve on the innovations of others. Spillovers might also take the form of transfers of knowledge among different types of institutions that undertake research—for example, a flow of information from universities to firms engaged in R&D, and vice versa. In addition, numerous case studies have documented the contributions to technical knowledge made by suppliers and customers, particularly in scientifically and technologically based industries. Perhaps less common but potentially significant are spillovers among firms that are part of the same industry but located in different countries. In each case, the likelihood of an idea spilling over to others will be a function of proximity, either geographic or technological.[27] (Technological proximity is a measure of the degree to which technologies used by different firms or industries are related.)

Spillovers have potentially important implications for economic models.[28] Specifically, they raise the possibility that R&D's contribution to the growth of productivity is disproportionate to its size. Although it only makes up a small portion of expenditures in the private economy, R&D could have a large effect on the growth of TFP. Indeed, if the spillover effect was big enough, it could imply the existence of increasing returns to scale at the aggregate level, meaning that a given percentage increase in the factors of production will lead to a larger percentage increase in output. The existence of increasing returns to scale opens up the possibility of endogenous growth—that is, perpetual growth in per capita income without the need to assume exogenous technological change. Paul Romer (1990), for example, developed models in which knowledge creation through R&D was the fundamental driver of technological change and (under certain conditions) endogenous growth.

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26. See CBO (1994) for a more complete discussion. See also Grossman and Helpman (1991) or Aghion and Howitt (1998) for additional detail on endogenous innovation models.

27. See Cohen (1995, p. 221), Verspagen (1995, p. 119), and Hall (1996, pp. 140-141).

28. Spillovers may also have implications for government policy. If the social return to R&D spending exceeds the private return, private markets will not supply the socially optimal amount of R&D—which constitutes a rationale for the government to subsidize R&D efforts. That particular implication of R&D spillovers will not be addressed in this paper.

There is little doubt that spillovers exist; the only question is whether they are significant at the macroeconomic level. Casual observation reveals many examples of new products, processes, or ideas that have been copied by rivals without paying compensation to the original inventor. That observation is confirmed by case studies (for example, Mansfield and others, 1977) of specific industrial and agricultural innovations, which generally find that the social benefits of an innovation exceed by a wide margin the benefits accruing to the original innovator. Case studies do not, however, establish the overall significance of spillovers.

To estimate the magnitude of spillovers associated with R&D spending, researchers use one of three basic methods. First, by using a specification that is based on a standard production function, the presence of spillovers can be inferred if the estimated rate of return to R&D spending is significantly higher than the return to ordinary capital or if the return to R&D rises when the equation is estimated using data that have a greater degree of aggregation. (That is, if spillovers to R&D exist within an industry, then the estimated returns to R&D will be higher when computed using industry-level rather than firm-level data.)[29]

Second, analysts have gauged spillovers by including specific variables that are designed to measure spillover benefits directly. For example, a researcher using firm-level data might include the industrywide stock of R&D, in addition to the firm's stock of R&D, as a proxy for industry-specific knowledge. Alternatively, equations could include the aggregate stock of R&D capital in the overall economy or, as is more commonly done, create an aggregate R&D stock by weighting the R&D stocks of alternative industries according to their technological proximity to the first firm or industry. Of course, calculating that proximity—which is an indicator of how related their technologies are—is a difficult task. One method is to estimate the stock of "borrowed" R&D of a firm or industry on the basis of purchases of inputs from other industries that perform R&D.[30] Additional methods use information on rates of cross-referencing of patents to deduce the technological distance between firms and to determine the "direction" of the spillovers. Another approach is to use the flows of imports and exports to infer the direction of spillovers across national boundaries.[31]

Third, it is possible to use cost functions to explore the effects of spillovers on the costs or structure of production in receiving firms or industries. Under that approach, the production costs of a firm or industry are related to output, relative factor prices, and the quantity of inputs, including the "own" stock of R&D capital and the R&D stock from other firms or industries. (That latter variable is meant to capture the spillover from external research efforts.)[32]

What does the empirical evidence say about the significance of spillovers? As described earlier, some studies that employed a standard production function approach found a very high return to own R&D, at least with cross-sectional data at the firm or industry level. Although such findings certainly suggest the presence of spillovers, the myriad of measurement and sta-

29. The ideas in this paragraph are drawn from Nadiri (1993). Note that this discussion excludes the results from case studies and empirical studies that measure the social returns to agricultural research.

30. See Terleckyj (1974, 1980), Sterlacchini (1989), and Coe and Helpman (1995).

31. Examples include Scherer (1982, 1984), Jaffe (1986, 1988), and Coe and Helpman (1995).

32. For more details, see Australian Industry Commission (1995, p. QA-6) and Nadiri (1993, pp. 16-17).

tistical problems associated with those studies raises the possibility that the spillover effect might be overstated. As noted earlier, measurement problems can lead to confusion about whether true spillovers are being captured by studies of this type. If the price index for the output of an R&D-intensive industry is not adjusted to reflect changes in quality and that output is used as an input to a second industry, what looks like a spillover could actually be a case of misattributed productivity. Moreover, under the assumption that all variables are measured correctly, excess returns could be merely a premium being received by innovators to compensate them for the inherent riskiness of R&D projects, many of which do not pay off.

On the question of whether the returns to R&D are greater at the industry than at the firm level, as might be expected if spillovers were present, there appears to be little systematic difference in the rates of return computed at different levels of aggregation. Studies that use firm-level data estimate returns to R&D that lie in roughly the same range as those estimated by using industry-level data (Australian Industry Commission, 1995, p. QA-37). According to Zvi Griliches (1992, 1995), two factors may account for the lack of difference. First, different rates of depreciation may be relevant at different levels of aggregation. When the return to R&D is estimated using an equation such as equation (5), it includes a depreciation component. The rate of depreciation that is relevant to an individual firm may be much higher than the rate that is relevant to an entire industry. (The rate of obsolescence will be greater for a firm than for an industry because it is easier for a firm to imitate another firm than for an industry to come up with a close substitute for a different industry's innovative output.) Second, different estimates of R&D capital will be relevant at different levels of aggregation because they will be calculated by using different rates of depreciation.

Studies that seek to measure spillovers directly—through the use of input purchases, patent data, or cost functions—have had more though not unqualified success. To varying degrees, those studies tend to find evidence of spillovers at both the firm and industry levels. For example, several early research efforts (Terleckyj 1974, 1980) used purchases of capital goods and other materials to measure the flow of technology among firms and industries.[33] A typical result from those studies is the finding that the return to borrowed R&D (that is, R&D emanating from other firms or industries) is higher than that of own R&D. Similarly, studies that use patent data to measure the technological distance between firms generally find evidence of spillovers, although not without exception. For example, in a pair of studies, Adam Jaffe (1986, 1988) found that a firm's productivity varied positively with the R&D of firms in the same technological cluster.[34] By contrast, at least one study of R&D and productivity growth in the United Kingdom found that the impact of knowledge spillovers (spillovers that are not embodied in inputs) arising from technological neighbors is extremely modest. (For more details, see Geroski, 1991.)

Studies that use cost functions have also found evidence of spillovers. Jeffrey Bernstein, for example, in two studies of the influence of R&D on the costs of production (1988, 1989),

33. Griliches and Lichtenberg (1984a) argue that these are not true spillovers because the price indexes used to deflate nominal purchases are not fully adjusted for quality.

34. Jaffe's research also suggests that spillovers may have a geographic component. For example, in his 1989 study, he found that local firms benefited more from academic research than distant firms did, whereas Jaffe, Trajtenberg, and Henderson (1993) found that geographic spillovers existed for manufacturing firms. Similar results were reported by Acs, Audretsch, and Feldman (1994); Adams and Jaffe (1996); and Audretsch and Feldman (1996).

found evidence of both intra- and interindustry spillovers in Canadian manufacturing industries.[35] In addition, Bernstein's results indicated that spillovers tended to be greater among related industries and that R&D undertaken in one industry can affect the productivity of multiple industries.

If knowledge can disperse among sectors that trade with one another in the domestic economy, then knowledge may spill over international boundaries as well. Indeed, some models of endogenous growth stress the link between international trade and productivity growth. Such models incorporate the assumption that trade gives less developed countries access to technological knowledge created by more advanced nations. Although many models assume that knowledge passes without cost to the entire world, it seems likely that the contacts developed through commercial exchange play an important role in knowledge diffusion. The larger the volume of trade, the greater the number of personal contacts and the faster the diffusion of knowledge.[36]

Empirical evidence strongly suggests the existence of international spillovers. For instance, in their seminal paper, David Coe and Elhanan Helpman (1995) regressed TFP on measures of foreign and domestic R&D stocks for 22 industrialized countries and found that a country's level of TFP depended not only on the stock of domestic R&D but also on the R&D stock of its trading partners. Moreover, they found evidence that in large countries, the stock of domestic R&D affected TFP more strongly, whereas in small countries, the foreign R&D stock had the larger influence. Coe and Helpman concluded that "[foreign] R&D may have a stronger effect on domestic productivity the more open an economy is to international trade" (p. 875). Subsequent research has largely affirmed their results regarding spillovers and the role of trade.[37]

The empirical findings related to international spillovers are not uniform, however. Not all studies have found that such spillovers are statistically significant, and of those that do find an effect, estimates of its size vary sharply among countries, with most of the benefits accruing to less developed nations.[38] As a result, it is not clear that the evidence on international spillovers is relevant for a large, technologically advanced country such as the United States. Indeed, some studies of bilateral spillovers (as discussed in Luintel and Khan, 2004) suggest that knowledge spillovers may actually be harmful to the United States.

Estimates of the spillovers associated with R&D spending are subject to the same measurement and estimating problems that afflict studies of the private return to R&D. However, two additional issues must be considered. First, researchers have found that R&D spillovers are not entirely cost free. To use the knowledge obtained through spillovers in their own produc-

35. That work was extended in Bernstein and Nadiri (1991) and Bernstein and Yan (1997). Further evidence of spillovers was presented in Bernstein and Nadiri (1988, 1989).

36. The argument in this paragraph is based on Cameron (1998). For more details about models of endogenous growth, see Aghion and Howitt (1998).

37. Examples include Bernstein and Yan (1997); Coe, Helpman, and Hoffmaister (1997); Engelbrecht (1997); Lichtenberg and van Pottelsberghe de la Potterie (1998); Xu and Wang (1999); van Pottelsberghe de la Potterie and Lichtenberg (2001); and Luintel and Khan (2004).

38. For more details, see Australian Industry Commission (1995); Keller (1998); Kao, Chiang, and Chen (1999); van Pottelsberghe de la Potterie and Lichtenberg (2001); and Luintel and Khan (2004).

tion processes, firms must have their own laboratories and staffs of scientists and engineers. That is, firms (and countries) that invest in R&D are better able to assimilate spillovers than firms that do not. If that is so, then the cost-reducing effect of spillovers may be exaggerated because whether the "own" or the "borrowed" R&D is providing the benefit is unclear.[39] At the national level, a country's ability to take advantage of spillovers may be related to its level of education (Verspagen, 1995, p. 119).

Second, the problem of lags, although difficult in the case of own R&D, is severe with regard to R&D spillovers. As noted earlier, the delay between when a firm invests in R&D and when the investment provides any benefit may be long and variable. It will take even longer for knowledge or innovation to transfer to other firms, industries, or countries. According to Griliches (1995):

> *The usual procedure—constructing an aggregate spillover pool—ignores the possibility that spillovers take more time than "own" effects, both because of secrecy and the time it takes for them to be expressed in new products and processes and diffused throughout the relevant industrial structure. Given the diffuse nature of such effects and the likely presence of long and variable lags, it is not surprising that "significant" findings are rare in this area (p. 70).*

A true dynamic analysis of the lags involved would require data that are frequently unavailable. To address that problem, some studies lag their R&D variable by one or more years. Others, however, do not (Australian Industry Commission, 1995, p. QA-19).

In summary, the available empirical evidence supports the idea that spillovers exist at the macroeconomic level and that they probably cross national boundaries. Indeed, it would be hard to believe that spillovers did not exist, considering the characteristics of knowledge and R&D capital that resemble those of public goods. But the challenges of measuring and estimating the impact of spillovers are formidable. Hence, it is not surprising to find considerable variation in estimates of the size of spillover effects and in the significance of those estimates across studies. Nevertheless, most surveys of the empirical literature conclude that spillovers exist. For example, Zvi Griliches (1995) asserts that:

> *. . . there has been a significant number of reasonably well done studies all pointing in the same direction: R&D spillovers are present, their magnitude may be quite large, and social rates of return remain significantly above private rates. . . . The estimated social rates of return look, actually, surprisingly uniform in their indication of the importance of such spillovers (p. 72).*

In his 1993 survey article, Ishaq Nadiri comes to the same conclusion:

> *As to the question of the existence and magnitudes of R&D spillovers, the evidence points to sizable spillover effects at the firm and industry levels. These effects are also present and likely to grow rapidly among firms in different countries. The spillover effects of R&D are*

39. See Cohen and Levinthal (1989) or Griffith, Redding, and Van Reenen (2004) for more on the idea that firms invest in R&D to generate new knowledge and to develop absorptive capacity. Jaffe (1986) provides some evidence to support that hypothesis. Mohnen (1992) asserts the same findings for R&D across national boundaries—that domestic R&D is necessary for a country to be able to assimilate foreign R&D.

often much larger than the effects of own R&D at the industry level. The indirect and social rates of return often vary from 20% to over 100% with an average somewhere close to 50% (p. 35).

Most authors, however, tend to hedge their conclusions, perhaps mindful of the measurement difficulties and the paucity of evidence from macroeconomic studies. Griliches (1995), for example, cautions the reader that the empirical studies capture only contributions of R&D that are measured in the national statistical accounts and that "[i]n spite of a number of serious and promising attempts to do so, it has proven very difficult to estimate the indirect contribution of R&D via spillovers to other firms, industries, and countries" (p. 83).

Evidence from Growth Accounting Studies

The evidence from empirical studies that estimate the private and social return to R&D strongly suggests that R&D spending contributes to productivity growth but difficulties associated with measurement and estimation make it hard to garner significant results, especially for studies that use a time-series or macroeconomic framework. One response is to sidestep the statistical problems and set up a model that uses economic theory (or outside evidence) to impose the parameters of the aggregate production function, including the R&D elasticity, and then analyze the implications that flow from that model. Growth accounting studies are a prime example of that approach, and calibrated models are another. Such models seek to answer such questions as, if the R&D elasticity is, say, 0.05, then what proportion of productivity growth can be attributed to R&D spending? Or, can the productivity slowdown of the 1970s be explained by lower R&D spending? Unfortunately, the implications of those types of studies for such big-picture questions depend heavily on whether or not the analyst assumes that the social returns to R&D are large.

The Contribution of R&D to Productivity Growth

Growth accounting studies estimate the contribution of R&D to productivity growth by apportioning the growth of GDP into contributions from each of the factor inputs and from total factor productivity. Because TFP is calculated as a residual, it is by definition the portion of the growth of output that is not explained by the growth of labor and capital. Growth accountants calculate the contribution from each factor input as the growth in that input multiplied by the output elasticity of that input. The elasticity of output with respect to each factor input is, in turn, approximated by using the income share of that input.

Although not without some complications, calculating the income shares of labor and capital is relatively straightforward because estimates of wages, hours, and total compensation are available for the industrialized countries. For example, payments to labor in the United States average about 70 percent of income, which means that the output elasticity of labor is 0.70. Therefore, under the assumptions of growth accounting, a 1 percent increase in labor hours would raise the level of output by 0.7 percent. Calculating the share of national income paid to owners of capital is more difficult but still possible. By contrast, the return to R&D is not split out from other components of capital income, so it is difficult to assign an income share to R&D.

However, if one is willing to assume a value for the rate of return to R&D (perhaps by using an estimate implied by the empirical studies surveyed earlier), then R&D may be added to the growth accounting framework by imposing a constant value for its rate of return. That was

the approach followed by the Bureau of Labor Statistics (BLS) in a 1989 study of the impact of R&D on productivity growth. In that study, analysts calculated an R&D stock using assumptions about depreciation rates, lags, and deflators that reflected consensus values from the empirical literature. On the basis of that stock, BLS computed the contribution of R&D to productivity growth by using an assumed rate of return of 0.30, an estimate based on a survey of the empirical literature. That rate of return is interpreted as the direct effect of R&D—it includes the private return and any spillovers at the industry level but not spillovers across industries or national boundaries.

BLS found that R&D contributed a relatively small amount to productivity growth in the nonfarm business sector. According to the bureau's estimate, R&D accounted for 0.15 percentage points, on average, during the 1948-1973 period and 0.14 percentage points during the 1973-1987 period. (Growth of labor productivity averaged 2.5 percent during the earlier period and 0.9 percent during the later period, calculations based on data available when the BLS paper was published.) The contribution that R&D made to such growth was concentrated almost entirely in the manufacturing sector. It averaged about 0.5 percentage points for manufacturing in both periods and was essentially zero in the nonmanufacturing sector throughout the sample period.

Other analysts have arrived at slightly larger estimates of the contribution of R&D by using similar methods, but the impact of R&D remains modest. The results of such studies differ from those of BLS because the studies employed a broader measure of the R&D stock (by including government R&D, for example) or because they assumed a higher rate of return to R&D. Zvi Griliches (1973), for example, estimated that R&D contributed about 0.3 percentage points to TFP growth in 1970, although he cautioned that his estimate was likely to be an upper bound on the true contribution of R&D to productivity growth. A similar contribution was reported by Edward Denison (1979). More recently, Diego Comin (2004) found that R&D's contribution to the growth of productivity during the post-World War II period lay in a range between 0.3 and 0.5 percentage points. Similarly, in a growth accounting exercise performed using data from the Bureau of Economic Analysis's R&D satellite account, Barbara Fraumeni and Sumiye Okubo (2002) estimated that R&D accounted for 0.38 percentage points of the growth in real GDP during the 1961-2000 period. (Boskin and Lau, 1996, reported similar results using data for the 1961-1990 period.)

Under more-aggressive assumptions about the return to R&D—using an estimate of the social return to R&D from the upper end of the range of estimates, for example—the contribution of R&D could be much larger. In a 1984 study, John Kendrick estimated that R&D contributed 1.2 percentage points to productivity growth for the 1948-1973 period and 0.7 percentage points for the years 1973 to 1981. On the basis of results from a calibrated growth model, Zvi Griliches (1992, p. S44) argued that estimates in the empirical literature of the social return to R&D from the upper end of the range imply that R&D spending could account for nearly half of labor productivity growth and almost three-quarters of TFP growth during the postwar period.[40]

40. Jones (2002) found that R&D contributed between 1.0 and 1.5 percentage points to the growth of output during the 1950-1993 period—although he used a model that is not directly comparable with those used by Kendrick, Griliches, and the others.

Explaining the Productivity Slowdown of the 1970s

Among the empirical studies of the returns to R&D, those that used time-series data had the least success in finding a significant role for R&D in the growth of productivity. That result arises largely because the R&D stock is a smooth series: it varies little from year to year and thus cannot explain much of the year-to-year variation in growth, especially at the aggregate level. A natural question that comes to mind is whether changes in the R&D stock can explain low-frequency movements in the productivity data. That is, can they help explain changes in the long-run trend in productivity growth? Statistical techniques do not work for questions like that because there are not enough observations (changes in the long-run trend) to use for estimating.

Many of the growth accounting studies discussed above have addressed that question. Specifically, most of the authors tried to determine whether changes in R&D spending were responsible for the dramatic slowdown in U.S. productivity growth that started in the early 1970s. (After growing at an average annual rate of 2.8 percent between 1947 and 1973, labor productivity slowed to an average rate of 1.4 percent during the years 1973 to 1995.) The results from growth accounting studies on that question parallel the results on the contribution of R&D to productivity growth: studies that focused on the private return to R&D (and excluded government R&D) tended to find a small or nonexistent role for R&D in the productivity slowdown, whereas studies that expanded the definition of R&D capital to include government R&D or assumed substantial spillover effects found a larger role.

Examples of the former type of research include the 1989 BLS study, which attributed essentially none of the productivity slowdown to R&D, and an influential 1988 paper by Zvi Griliches, in which he concluded that consensus estimates of the elasticity of output with respect to R&D "are not large enough to account for more than a modest part of the observed slowdown in the growth of productivity" (p. 15).[41] By contrast, John Kendrick's 1984 study found that a sizable share of the slowdown—about 0.5 percentage points—could be attributed to slower growth in the R&D stock. A more modest estimate comes from Frederic Scherer (1983), who found that the portion of the productivity shortfall attributable to R&D was between 0.2 and 0.4 percentage points. In the growth accounting exercise described by Griliches (1992), the portion of the slowdown that was explained by R&D varied directly with the magnitude of the R&D spillovers that had been imposed in the model. In sum, the greater the social return to R&D, the larger the percentage of the slowdown that can be explained.

Discussion and Conclusion

Given that innovation is a fundamental source of technological change and therefore of productivity growth, there is little doubt that research and development—especially if defined broadly to include the invention of new products, the discovery of new ideas, and the improvement of business processes—is the root of all increases in productivity. Yet a broad definition of R&D is not very useful because it is impossible to measure every activity that increases the stock of knowledge. Hence, this paper concentrates on estimates of the impact of formal R&D on productivity growth.

41. In his paper in the *American Economic Review*, Griliches (1980a) calculated that R&D explained about one-tenth of the slowdown, or 0.14 percentage points.

To be sure, a casual reading of the literature indicates that the answer to the first question underlying this analysis—whether formal R&D is an important factor in explaining productivity growth—is yes. Although case studies were not surveyed for this analysis, in individual instances they have revealed extraordinary returns to investment in R&D. If researchers tend to select successful projects for their research, however, it is not clear that the results of that type of study will generalize to the overall economy. More useful evidence comes from econometric studies, which use statistical techniques to analyze the correlations between variables at the firm level, the industry level, or the level of the entire economy. Those studies will include all formal R&D projects, regardless of whether they proved successful. Results from econometric studies strongly suggest that R&D spending has a positive influence on productivity, with a rate of return that is likely to exceed that on conventional investments. The existence of any positive results is impressive when one considers the complexity of the relationship between R&D and productivity and the daunting measurement and estimating challenges associated with R&D. Perhaps as a result of those challenges, however, the size of the impact from different studies varies over a wide range, depending on the data sample, the period, the form of the equation, and the industry being examined.

Although econometric studies use a variety of methods, differences in their samples and in the specification of their estimated equations seem to matter less in estimating the R&D elasticity than differences in the type of data used for the calculation. Almost all of the studies that report a positive and significant R&D elasticity use cross-sectional rather than time-series data. Those studies generally find that R&D capital is a significant contributing factor to differences in productivity among firms, although that result is largely confined to the manufacturing sector and possibly to industries in scientific sectors.

Some of the cross-sectional estimates of the return to R&D suggest a very strong payoff to R&D investments—as much as two or three times the return to investments in physical capital. One question that immediately arises is how such a gap could persist for such a long time. One would expect that the return to R&D would exceed that on conventional investments because R&D is a very risky activity. A large proportion of R&D projects fail, and among those that succeed, the possibility exists that a competitor will imitate the innovation and erode the return. However, if the true rate of return to R&D was at the upper end of the range of estimates, one would expect companies to invest in R&D until the return was driven down, closer to the returns to other types of investment. (Griliches, 1995, p. 82, discusses that issue in more depth.)

Results from time-series estimates of productivity equations have proved less conclusive than results from equations that use cross-sectional data, with estimated coefficients that are much smaller and often statistically insignificant, especially as the degree of aggregation rises. (Results at the economywide level are less definitive than those at the industry level, which in turn are generally weaker than the results from firm-level studies.) Such results are mildly troubling because results from time-series equations are more relevant than cross-sectional findings for long-term models of the economy. As noted earlier, the rationale for why the coefficients should differ between the cross-sectional and the time-series estimates is not apparent. Although economists have yet to fully reconcile the difference, some possible explanations have been put forward.

The most likely explanation is that the estimate of the coefficient on R&D spending in cross-sectional studies is biased as a result of omitting one or more variables that differ across firms or industries. If there is a characteristic or aspect of a firm or industry that influences productivity and is related in some way to R&D spending, then omitting that characteristic will bias the ordinary least squares estimate of the R&D elasticity. For instance, if firms that are successful (that is, productive) for reasons other than R&D tend to spend more of their money on "luxuries" such as R&D, there will be differences in productivity among firms that are correlated with R&D, and the true coefficient on R&D in a standard equation such as equation (2) will be biased upward (Griliches, 1995, p. 58). Of course, researchers try to control for such unobserved differences between firms or industries, but they often lack the necessary data to do so.

In a related example, Richard Nelson (1988) has argued that a cross-sectional correlation will arise if differences exist among industries in their degree of "technological opportunity," or inherent capacity for technological advances. In that case, stronger technological opportunity will lead to faster growth of TFP and induce more R&D spending, thus causing a positive correlation between TFP and R&D spending in cross-sectional data. However, an important implication of Nelson's model is that an increase in R&D spending in any given industry will not lead to faster TFP growth.

Another possibility is that the significance of the cross-sectional estimates arises from increases in market share rather than aggregate productivity. If R&D spending allows firms to increase their share of a market—raising their sales at their rivals' expense—then cross-sectional regressions could show a positive effect because firms in the industry with higher R&D expenditures will have higher levels of sales and therefore higher levels of productivity. However, the industry overall will not have experienced an increase in productivity because the gains and losses will cancel each other out (although it is possible that productivity will eventually rise as less-productive firms go out of business). One implication of that phenomenon is that an increase in R&D spending by all firms in an industry will not lead to increases in productivity for any individual firm in the industry.[42]

Last, the pattern of results may arise from a combination of influences rather than a single factor. That is, the size and significance of the cross-sectional estimate of the R&D elasticity may be larger than the true elasticity because of battles for market share and because of upward bias stemming from omitted variables. It also seems likely that the statistical problems that were outlined for the time-series estimates—including multicollinearity and simultaneity—make the size and significance of the estimated elasticities look smaller than they truly are.[43] Time-series estimates of the economywide production function—even those outside of the R&D literature—frequently yield coefficients that are insignificant or inconsistent with the predictions of economic theory.

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42. Measurement problems may have induced spurious results in cross-sectional studies that use plant-level or firm-level data. Some analysts have argued that because of the way that output and inputs are measured, large firms are likely to have high levels of (measured) productivity, even if their true productivity is close to the industrywide average. If larger firms tend to undertake more R&D than smaller firms do, then the correlation between R&D and productivity in cross-sectional studies may be an artifact of the way that productivity is measured. For more details, see Katayama, Lu, and Tybout (2003).

43. See, for example, Hall and Mairesse (1995), who argue that their corrections for bias in cross-sectional equations lower the estimated coefficient, bringing it closer to the time-series estimates.

The wide range of estimates of the R&D elasticity makes it hard to answer the second question underlying this analysis—that is, how large an impact does R&D have on productivity? If it was necessary to pick a single number to use in macroeconomic models, a reasonable strategy would be to choose a value that lay within the central tendency of the estimates from the empirical literature. Choosing a value in the middle of the range is consistent with the presumption that the rate of return to R&D is slightly higher than that on other types of corporate spending. That strategy rules out an elasticity estimate of zero, which would imply that R&D investment had no effect on productivity and was therefore systematically unprofitable. It also rules out estimates at the upper end of the range, which are unrealistic because they would be unlikely to persist for long periods of time. Thus, an estimate of the rate of return of between 0.20 and 0.30 would be reasonable, which would imply an output elasticity of R&D that would lie between roughly 0.02 and 0.05.

It is possible to interpret the strategy of using an estimate of the rate of return to R&D of between 0.20 and 0.30 as being overly conservative or overly aggressive. It could be construed as conservative because it assumes that spillovers play a modest role at the aggregate level. Although there is some evidence of very strong spillovers—indicated by very high rates of return to R&D—an estimate near the middle of the overall range seems more plausible. The strategy could be interpreted as being overly aggressive because it gives results based on cross-sectional data more weight than results based on time-series data, even though the latter type of estimate conforms more closely to the needs of macroeconomic models. However, analysts have had relatively little success in estimating time-series equations using aggregate data.

Turning to the third question driving this analysis—whether it is worthwhile to add R&D capital to macroeconomic models of the economy—the answer is somewhat clearer. The use of an estimate of the R&D elasticity from the middle of the presumed range makes it seem unlikely that adding R&D to such models will improve forecasts of productivity growth, increase understanding of its historical behavior, or aid in policy simulations. Using consensus estimates of parameters, growth accounting studies have shown that R&D spending makes a small, steady contribution to economic growth. Therefore, unless one is willing to assume large spillovers, the inclusion of R&D in macroeconomic models will have little effect on economic forecasts or policy simulations. Moreover, its inclusion in models does not increase understanding of the historical behavior of productivity. The stock of R&D capital displays relatively little variation on a quarterly or annual basis; as a result, it cannot explain much of the time-series variation in productivity at those frequencies. In addition, R&D does little to explain low-frequency changes in data, including the post-1973 slowdown in productivity and the pickup in productivity growth that commenced in the mid-1990s.

Finally, it is not clear that adding R&D to macroeconomic models will improve their forecasts or projections. Under CBO's current estimating method, for example, the effect of R&D on productivity is included in the estimate of TFP. If an increase in R&D spending does, in fact, raise aggregate productivity, then TFP should grow faster. If there was an increase in R&D over a long period—say, 10 years—then the uptick in R&D would be reflected in potential TFP, which is a measure of the trend in TFP. Therefore, CBO's forecast of potential TFP implicitly includes the effects of R&D spending (and any other variable that affects TFP but is not explicitly included in the model), albeit in an attenuated form. Although the effects of R&D are buried in the current method, it is not clear that a separate forecast of the R&D stock would improve the forecast of TFP relative to CBO's current procedure. And that con-

sideration leaves aside the question of whether it is possible to adequately model the determinants of R&D spending so as to be able to forecast the R&D stock.

In short, the benefits of adding R&D to macroeconomic models probably do not exceed the costs of doing so. Data and methods in this area have improved during the past 20 to 30 years and will continue to do so. Quite possibly, in time, analysts will be better able to identify the impact of R&D on productivity.

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